## Linear Programming

- A large class of optimization problems in which the constraints and optimization criterion are linear functions.
- A *Linear Programming*(*LP*) problem consists of assigning real values to variables such that these variables
  - 1. (Linear constraints) satisfy a set of *linear* equalities or inequalities, and
  - 2. (**Objective function**) maximize or minimize a given *linear* objective function.

- Example: A cottage industry makes two kinds of products  $P_1$  and  $P_2$ . The daily demand for  $P_1$  is 100 and the daily demand for  $P_2$  is 200. The total amount of items that the industry can produce in a day is 250. The industry makes profit of Rs. 1 per unit item of type  $P_1$  and Rs. 5 per unit item of type  $P_2$ . How many items of  $P_1$  and  $P_2$  should the industry produce to make maximum amount of profit?
- Let  $x_1$  be a variable denoting the amount of  $P_1$  items produced by the industry and  $x_2$  the mount of  $P_2$  items.
- The goal is to maximize the *linear objective function*:

$$1 \cdot x_1 + 5 \cdot x_2$$

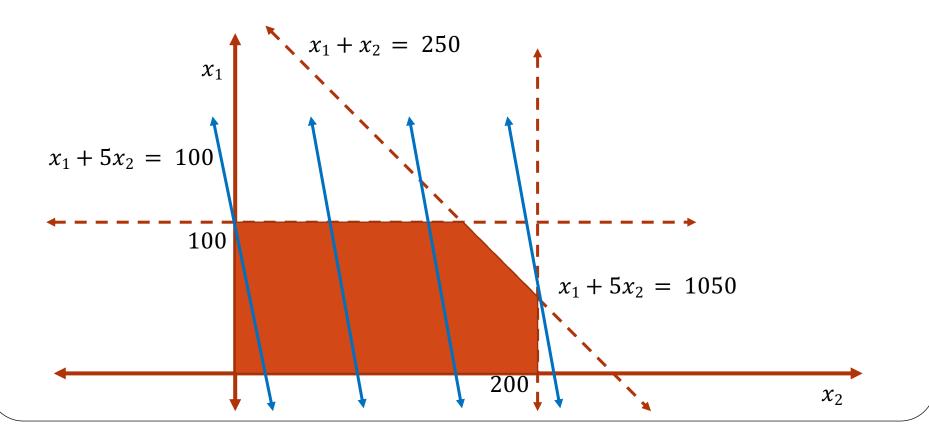
under the *linear constraints*:

 $x_1 \ge 0, x_2 \ge 0, x_1 \le 100, x_2 \le 200, x_1 + x_2 \le 250$ 

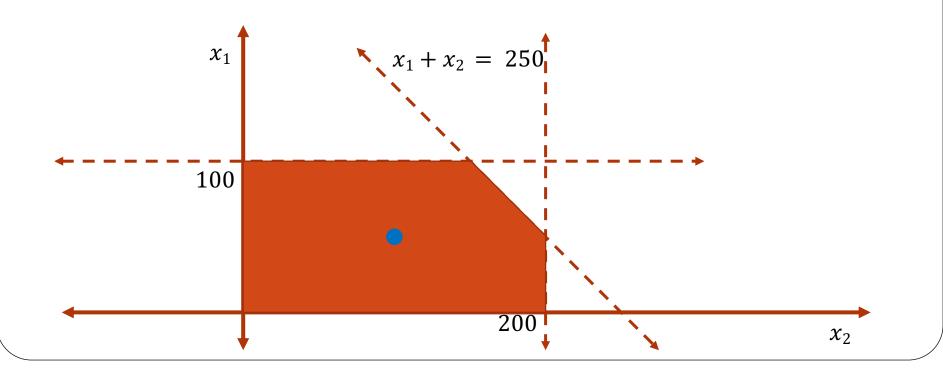
• <u>Problem(LP)</u>: Maximize the *linear objective function*:  $1 \cdot x_1 + 5 \cdot x_2$ 

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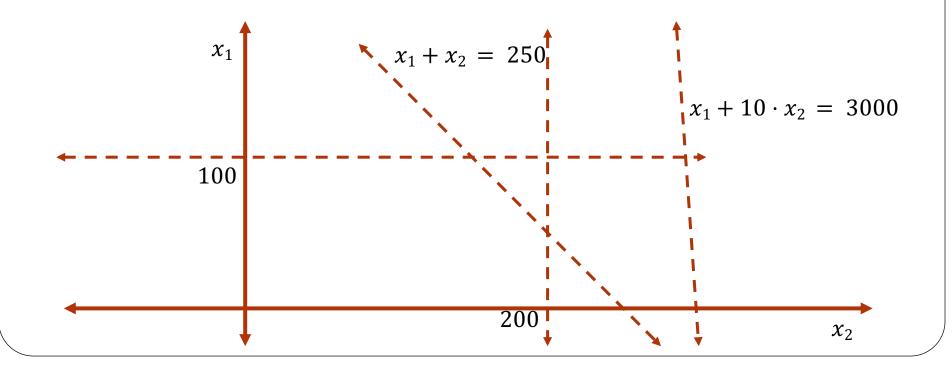
- Given a Linear Programming problem, we will use the following definitions:
  - <u>Feasible solution</u>: An assignment to the variables that satisfy all the linear constraints.
  - Example:  $x_1 = 50, x_2 = 100$  is a feasible solution.



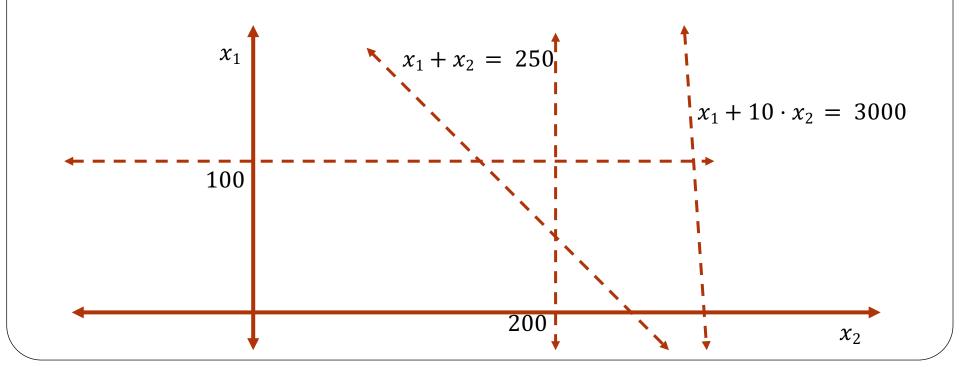
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  - Not necessarily. Suppose the linear constraints are  $x_1 \ge 0, x_2 \ge 0, x_1 \le 100, x_2 \le 200,$  $x_1 + x_2 \le 250, x_1 + 10 \cdot x_2 \ge 3000$

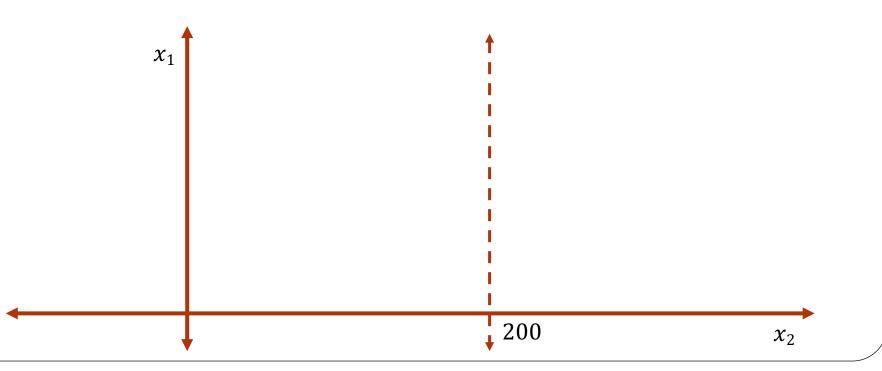
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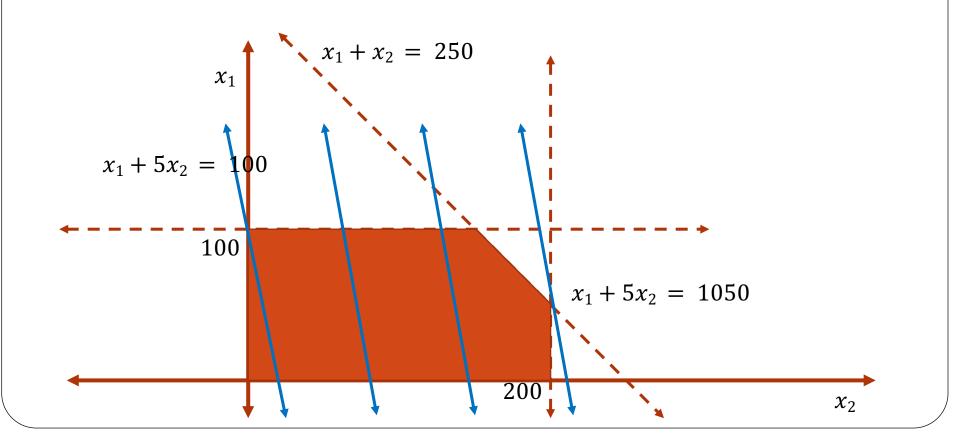
• <u>Infeasible LP</u>: A linear program is said to be infeasible if there are no feasible solutions.



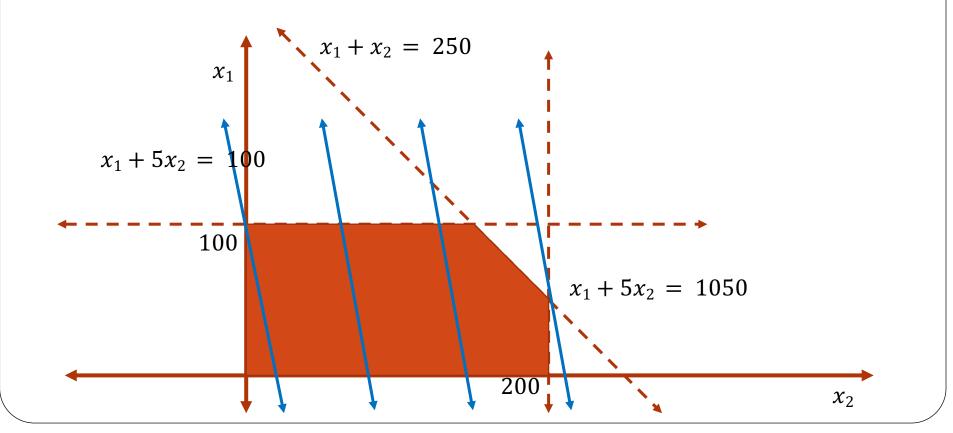
- <u>Unbounded LP</u>: A linear program is said to be unbounded if it is possible to achieve arbitrarily high values of the objective function.
  - <u>Example</u>: Maximize  $(x_1 + 5 \cdot x_2)$ subject to  $x_1 \ge 0, x_2 \ge 0, x_2 \le 200$ .



• <u>Claim</u>: For any linear program that is not infeasible and unbounded, the objective function value is maximized at one of the *vertices* of the feasible region.

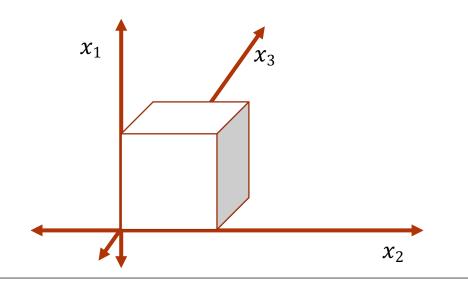


- Naïve idea for solving an LP:
  - Try all possible vertex of the feasible region and return the one that maximizes the objective function.



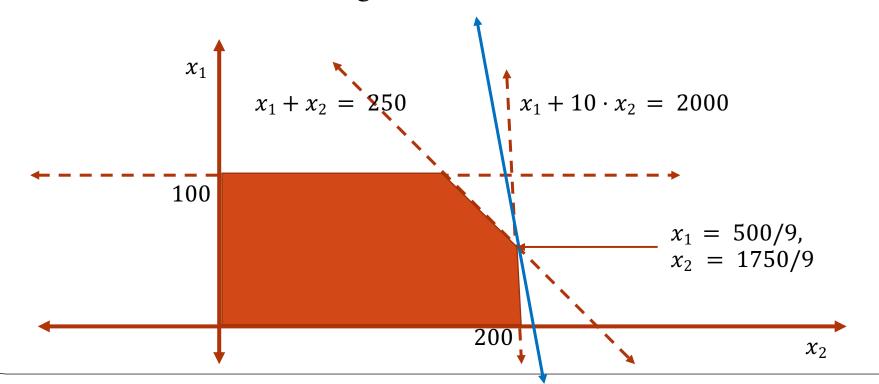
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  - Try all possible vertex of the feasible region and return the one that maximizes the objective function.
  - Suppose the LP has n variables and m = O(n) constraints. How many vertices can the feasible region have in worst case?
    - Exponentially many! Consider the LP: maximize  $(x_1 + x_2 + \dots + x_n)$ subject to  $0 \le x_1, x_2, \dots, x_n \le 1$ .



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- The optimal solution may assign real numbers to some variables even though all of the constraints of objective function involve integers.
- Suppose in addition to the linear constraint, we add another constraint that all the variables should be integers. Such linear programs are called Integer Linear Programs (ILP).
- Integer Linear Program(ILP): Consists of
  - Linear objective function
  - Linear constraints.
  - All variables should be integers.

<u>Decision-ILP</u>: Given the above and an integer k, determine if there is an integer assignment to the variables such that the objective function value is at least k.

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- <u>Claim</u>: Decision-ILP is **NP**-complete.
  - Proof:
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      - <u>Proof idea</u>: Given a 3-SAT formula, we construct an instance of Decision-ILP.

For each clause (e.g.,  $(x_1 \lor x_2 \lor \lor x_3)$ ) we create a linear constraint (e.g.,  $x_1 + 1 - x_2 + x_3 \ge 1$ ). We further consider constraints  $0 \le x_1, \dots, x_n \le 1$  and that all variables are integers.

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- Formulating problems as an ILP is a standard way of solving many combinatorial problems.
- <u>Example</u>: Maximum Independent set.
  - Consider a 0 1 variable for each vertex, 1 denoting inclusion. For each edge (x, y), there is a constraint that  $x + y \leq 1$ .

# Linear Programming

Solving problems by formulating as Linear Programs

# Linear Programming: Applications

- We saw how some combinatorial problems can be formulated as an **Integer** Linear Programming (ILP) problem.
- Unfortunately, ILP is hard.
- A number of problems can be formulated as a Linear Programming problem and we know there is a polynomial time algorithm for LP.
- Some interesting applications:
  - Shortest s t path in a directed graph with non-negative weights.
  - Maximum flow in a network graph.

### Linear Programming: Applications

- <u>Problem (Maximum S t flow</u>): Given a network graph G = (V, E) with special source S and sink t, find the maximum value of an S t flow in the graph.
- Let m = |E|. We use m variables, one for each edge.
- For an edge (u, v), we will use variable  $f_{uv}$  to denote the flow along the edge (u, v).
- We construct the following LP given G.
  - Maximize  $\sum f_{sv}$
  - Subject to,  $s, v \in E$ 
    - $f_{uv} \leq c(u, v)$ , for all (u, v) in E.
    - $\sum_{(v,u)\in E} f_{vu} = \sum_{(u,v)\in E} f_{uv}$ , for all u in  $V \{s,t\}$ .
    - $f_{uv} \geq 0$ .

## Linear Programming: Applications

- <u>Problem (Shortest S t path</u>): Given a weighted, directed graph G = (V, E). Find the length of the shortest path from vertex S to vertex t.
- Let n = |V|. We use n variables, one for each vertex.
- For a vertex v, we will use variable  $d_v$  to denote the length of the shortest path from vertex s to vertex v.
- We construct the following LP given G.
  - *Maximize*  $d_t$ ,
  - subject to:
    - For all edges  $(u, v) \in E, d_v \leq du + w(u, v)$ .
    - $d_s = 0$ .

# Linear Programming

Solving an LP

- To be able to design an algorithm for solving LP problems, it will be useful if we define problems more precisely in some standard format.
- <u>Standard form</u>: A Linear Program is said to be *standard form* if the following holds:
  - 1. The linear objective function should be *maximized*.
  - 2. All variables have non-negativity constraint. i.e., for all  $i, x_i \ge 0$ .
  - 3. All the remaining linear constraints are of the following form:  $\sum_{j=1}^{n} a_j \cdot x_j \leq b_j$

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  - 3. All the remaining linear constraints are of the following form:  $\sum_{j=1}^{n} a_j \cdot x_j \leq b_j$
  - <u>Question</u>: Is there a way to convert any LP problem to an *equivalent* standard form?
    - <u>Equivalence of LP's</u>: Two LP problems P1 and P2 are said to be equivalent if for any feasible solution for P1 with objective value *Z*, there is a feasible solution of P2 with the same objective value and vice versa.

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- A general LP problem might not be in standard for because it might have:
  - 1. Equality constraints (=) rather than inequality ( $\leq$ ).
  - 2.  $\geq$  instead of  $\leq$ .
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    - <u>Idea</u>: Replace a variable x (that has no non-negativity constraint) with (x' x'') everywhere and put  $x' \ge 0$  and  $x'' \ge 0$ .
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  - 4. Minimization rather than maximization.
    - <u>Idea</u>: Replace "Minimize  $\sum c_i x_i$ " with "Maximize  $\sum (-c_i) \cdot x_i$ ".
    - In this case, equivalence of LP is in the sense that the objective values of LPs are negation of each other instead of being same. So, you can solve one to get a solution for the other.

- Example:
  - Minimize  $-2x_1 + 3x_2$
  - subject to
    - $x_1 + x_2 = 7$
    - $\bullet x_1 2x_2 \leq 4$
    - $x_1 \geq 0$

- Example: Minimize to Maximize
  - Maximize  $2x_1 3x_2$
  - subject to
    - $x_1 + x_2 = 7$
    - $\bullet x_1 2x_2 \leq 4$
    - $x_1 \geq 0$

- Example: non-negativity constraint for  $x_2$ 
  - Maximize  $2x_1 3(x_2' x_2'')$
  - subject to
    - $x_1 + (x_2' x_2'') = 7$ •  $x_1 - 2(x_2' - x_2'') \le 4$ •  $x_1 \ge 0, x_2' \ge 0, x_2'' \ge 0$

- Example: non-negativity constraint for  $x_2$ 
  - Maximize  $2x_1 3x_2' + 3x_2''$
  - subject to
    - $x_1 + x_2' x_2'' = 7$ •  $x_1 - 2x_2' + 2x_2'' \le 4$ •  $x_1 \ge 0, x_2' \ge 0, x_2'' \ge 0$

- Example: renaming variables
  - Maximize  $2x_1 3x_2 + 3x_3$
  - subject to
    - $x_1 + x_2 x_3 = 7$ •  $x_1 - 2x_2 + 2x_3 \le 4$
    - $x_1 \ge 0, x_2 \ge 0, x_3 \ge 0$

- Example: Equality to inequality
  - Maximize  $2x_1 3x_2 + 3x_3$
  - subject to
    - $x_1 + x_2 x_3 \le 7$ •  $-x_1 - x_2 + x_3 \le -7$ •  $x_1 - 2x_2 + 2x_3 \le 4$ •  $x_1 \ge 0, x_2 \ge 0, x_3 \ge 0$

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  - 1. The linear objective function should be *maximized*.
  - 2. All variables have non-negativity constraint. i.e., for all  $i, x_i \ge 0$ .
  - 3. All the remaining linear constraints are of the following form:  $\sum_{j=1}^{n} a_j \cdot x_j \leq b_j.$
- It will be useful to further convert an LP in standard for to an equivalent LP in *Slack form*.
  - <u>Slack form</u>: For every inequality  $\sum_{j} a_j x_j \leq b_j$ , we introduce a *slack* variable  $S_j$  and replace  $\sum_{j} a_j x_j \leq b_j$  with  $s_j = b_j \sum_{j} a_j x_j$  and  $s_j \geq 0$ .

• Example:

- Maximize  $2x_1 3x_2 + 3x_3$
- subject to

•  $x_1 + x_2 - x_3 \le 7$ •  $-x_1 - x_2 + x_3 \le -7$ •  $x_1 - 2x_2 + 2x_3 \le 4$ •  $x_1 \ge 0, x_2 \ge 0, x_3 \ge 0$ 

• Example: Standard form to slack form.

• 
$$z = 2x_1 - 3x_2 + 3x_3$$
  
•  $x_4 = 7 - x_1 - x_2 + x_3$   
•  $x_5 = -7 + x_1 + x_2 - x_3$   
•  $x_6 = 4 - x_1 + 2x_2 - 2x_3$   
•  $x_1 \ge 0, x_2 \ge 0, x_3 \ge 0, x_4 \ge 0, x_5 \ge 0, x_6 \ge 0.$ 

- The variables on the LHS are called *basic variables* and those on the RHS are called *non-basic variables*.
- <u>Basic solution</u>: Set all non-basic variables to **0** and compute the value of the basic variables.

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- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.

# Linear Programming:

The Simplex Algorithm

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:
  - $z = 3x_1 + x_2 + 2x_3$
  - $x_4 = 30 x_1 x_2 3x_3$
  - $x_5 = 24 2x_1 2x_2 5x_3$
  - $x_6 = 36 4x_1 x_2 2x_3$

• Use 
$$x_1 = (9 - x_6/4 - x_2/4 - x_3/2)$$

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:

• 
$$z = 3(9 - x_6/4 - x_2/4 - x_3/2) + x_2 + 2x_3$$

• 
$$x_4 = 30 - (9 - x_6/4 - x_2/4 - x_3/2) - x_2 - 3x_3$$

• 
$$x_5 = 24 - 2(9 - x_6/4 - x_2/4 - x_3/2) - 2x_2 - 5x_3$$
  
•  $x_1 = (9 - x_6/4 - x_2/4 - x_3/2)$ 

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:
  - $z = 27 + x_2/4 + x_3/2 3x_6/4$
  - $x_4 = 21 3x_2/4 5x_3/2 + x_6/4$
  - $x_5 = 6 3x_2/2 4x_3 + x_6/2$
  - $x_1 = 9 x_2/4 x_3/2 x_6/4$
- Now  $x_2$ ,  $x_3$ , and  $x_6$  are the non-basic variables and  $x_1$ ,  $x_4$ , and  $x_5$  are the basic variables.
- The objective value of the *basic solution* is now 27.
- <u>Claim</u>: If the basic solution is feasible for the LP before pivoting, then the basic solution for the LP after pivoting is also feasible.

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:
  - $z = 27 + x_2/4 + x_3/2 3x_6/4$ •  $x_4 = 21 - 3x_2/4 - 5x_3/2 + x_6/4$ •  $x_5 = 6 - 3x_2/2 - 4x_3 + x_6/2$ •  $x_1 = 9 - x_2/4 - x_3/2 - x_6/4$
- Use  $x_3 = 3/2 3x_2/8 x_5/4 + x_6/8$

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:
  - $z = 111/4 + x_2/16 x_5/8 11x_6/16$
  - $x_4 = 69/4 + 3x_2/16 + 5x_5/8 x_6/16$

• 
$$x_1 = 33/4 - x_2/16 + x_5/8 - 5x_6/16$$

- $x_3 = 3/2 3x_2/8 x_5/4 + x_6/8$
- Now  $x_2$ ,  $x_5$ , and  $x_6$  are the non-basic variables and  $x_1$ ,  $x_3$ , and  $x_4$  are the basic variables.
- The objective value of the *basic solution* is now 111/4.

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:

• 
$$z = 111/4 + x_2/16 - x_5/8 - 11x_6/16$$
  
•  $x_4 = 69/4 + 3x_2/16 + 5x_5/8 - x_6/16$   
•  $x_1 = 33/4 - x_2/16 + x_5/8 - 5x_6/16$   
•  $x_3 = 3/2 - 3x_2/8 - x_5/4 + x_6/8$ 

• Use 
$$x_2 = 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3}$$

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- Example:
  - $z = 28 x_3/6 x_5/6 2x_6/3$ •  $x_1 = 8 + x_3/6 + x_5/6 - x_6/3$

• 
$$x_2 = 4 - \frac{8x_3}{3} - \frac{2x_5}{3} + \frac{x_6}{3}$$

- $x_4 = 18 x_3/2 + x_5/2$
- Now the basic solution is the optimal solution.
- The optimal objective value for the initial LP is 28 and the value of the variables are  $x_1 = 8$ ,  $x_2 = 4$ , and  $x_3 = 0$ .

- <u>Simplex algorithm</u>:
  - Repeat:
    - **Pivot**: Rewrite the LP in slack form such that the objective value of the basic solution increases.
- We looked at a contrived example devoid of any complications. Here are some of the complications that could arise:
  - 1. What if the initial basic solution is not a feasible solution?
  - 2. What if the LP is unbounded? How and where do we detect this?
  - 3. What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?

#### • Complications:

- 1. What if the initial basic solution is not a feasible solution?
  - We will determine this in a preprocessing step. If the LP has a feasible solution, then we will rewrite it in a form where the basic solution is feasible.
- 2. What if the LP is unbounded? How and where do we detect this?
  - We will check this while pivoting.
- 3. What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?
  - This is indeed a problem with Simplex. The algorithm might cycle without increasing the objective value. Simplex is actually not a polynomial time algorithm but it is still used in practice because it works very well on real world instances.

- (*Complication 2*) What if the LP is unbounded? How and where do we detect this?
- Consider the following general slack LP that we obtain while running Simplex:
- $z = v + c_1 x_1 + c_2 x_2 + \dots + c_n x_n$
- $x_{n+1} = b_1 a_{11}x_1 a_{12}x_2 \dots a_{1nxn}$
- $x_{n+2} = b_2 a_{21}x_1 a_{22}x_2 \dots a_{2nxn}$
- $x_{n+m} = b_m a_{m1}x_1 a_{m2}x_2 \dots a_{mn}x_n$
- <u>Claim</u>: Suppose  $c_i > 0$  and  $a_{1i}, a_{2i}, a_{3i}, \dots, a_{mi} \leq 0$ . Then the LP is unbounded.

- (*Complication 3*) What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?
- Consider the following example:

• 
$$z = 8 + x_3 - x_4$$

• 
$$x_1 = 8 - x_2 - x_4$$

• 
$$x_5 = x_2 - x_3$$

• We have to pivot using  $x_3 = x_2 - x_5$  but that gives us

• 
$$z = 8 + x_2 - x_4 - x_5$$

• 
$$x_1 = 8 - x_2 - x_4$$

• 
$$x_3 = x_2 - x_5$$

• The objective value of the basic solution does not change.

- (*Complication 3*) What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?
- So, the Simplex may cycle between slack forms without increasing the objective value of the basic solution.
- <u>Claim</u>: Each slack form is uniquely determined by the set of basic and non-basic variables.
- <u>Question:</u> What is the upper bound on the number of slack forms that the Simplex cycles without increasing the objective value of the basic solution?

- (*Complication 3*) What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?
- So, the Simplex may cycle between slack forms without increasing the objective value of the basic solution.
- <u>Claim</u>: Each slack form is uniquely determined by the set of basic and non-basic variables.
- <u>Question:</u> What is the upper bound on the number of slack forms that the Simplex cycles without increasing the objective value of the basic solution?
  - ${}^{n+m}C_m$ . This is the upper bound on the number of different slack forms.

- (*Complication 3*) What if after a pivoting step the objective value of the basic solution does not increase? What is the running time of the Simplex algorithm?
- So, the Simplex may cycle between slack forms without increasing the objective value of the basic solution.
- <u>Claim</u>: Each slack form is uniquely determined by the set of basic and non-basic variables.
- <u>Claim</u>: If the Simplex fails to terminate in  ${}^{n+m}C_m$  steps, then it cycles.
- There is a way (*Bland's rule*) to choose the pivoting variables so that Simplex always terminates.

- (*Complication 1*) What if the initial basic solution is not a feasible solution?
- We construct the following LP, *L*' in slack form:
- $z = -x_0$
- $x_{n+1} = b_1 a_{11}x_1 a_{12}x_2 \dots a_{1nxn} + x_0$
- $x_{n+2} = b_2 a_{21}x_1 a_{22}x_2 \dots a_{2n}x_n + x_0$
- •
- $x_{n+m} = b_m a_{m1}x_1 a_{m2}x_2 \dots a_{mn}x_n + x_0$
- <u>Claim</u>: The given LP has a feasible solution if and only if the optimal objective value of *L*' is **0**.
- So, all we need to do is to solve *L*'. This seems to bring us back to the original problem. However, we see that *L*' is a *simple* LP.

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- $x_{n+m} = b_m a_{m1}x_1 a_{m2}x_2 \dots a_{mn}x_n + x_0$
- <u>Claim</u>: The given LP has a feasible solution if and only if the optimal objective value of *L*' is **0**.
- <u>Claim</u>: L' is feasible.
- The basic solution might not be a feasible solution since some  $b_i < 0$ .

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- The basic solution might not be a feasible solution since some  $b_i < 0$ .
- Let  $b_i$  be the smallest among  $b_1, \dots, b_m$ . We will pivot using  $x_{n+i} = b_i a_{i1}x_1 \dots + x_0$

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- <u>Claim</u>: The basic solution of the LP obtained after the above pivoting is a feasible solution.

- (*Complication 1*) What if the initial basic solution is not a feasible solution?
- Pre-processing algorithm:
  - Given L, check if all  $b_i$ 's are positive. In that case return L.
  - Consider L'. Perform the pivoting using the equation with smallest  $b_i$  to obtain L''.
  - Solve *L*" using Simplex and find the optimal objective value *Opt*.
  - If  $(Opt \neq 0)$ , then output "LP is infeasible".
  - Otherwise, let  $L_S$  be the LP obtained at the end of the simplex. Do the following:
    - If  $x_0$  is a basic variable in  $L_S$ , then perform a pivoting step to obtain  $L_S'$ .
    - Remove all instances of  $x_0$  and rewrite the objective function of L in terms of non-basic variables of  $L_s'$ .

- (*Complication 1*) What if the initial basic solution is not a feasible solution?
- Pre-processing algorithm: Example
- *L*:
  - $z = 2x_1 x_2$
  - $x_3 = 2 2x_1 + x_2$
- $x_4 = -4 x_1 + 5x_2$ • L':
  - $z = x_0$
  - $x_3 = 2 2x_1 + x_2 + x_0$
  - $x_4 = -4 x_1 + 5x_2 + x_0$
- *L''*: After Pivot using  $(x_4 = ...)$ 
  - $z = -4 x_1 + 5x_2 x_4$
  - $x_3 = 6 x_1 4x_2 + x_4$
  - $x_0 = 4 + x_1 5x_2 + x_4$

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  - $x_4 = -4 x_1 + 5x_2$
- $L_S$ : •  $z = -x_0$ 
  - $x_2 = 4/5 x_0/5 + x_1/5 + x_4/5$
  - $x_3 = 14/5 + 4x_0/5 9x_1/5 + x_4/5$

•  $z = 2x_1 - x_2 = 2x_1 - (4/5 + x_1/5 + x_4/5) = -4/5 + 9x_1/5 - x_4/5$ 

• 
$$x_2 = 4/5 + x_1/5 + x_4/5$$

• 
$$x_3 = 14/5 - 9x_1/5 + x_4/5$$

# End